Discover Artificial Intelligence

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Beyond the average association between artificial intelligence and sales performance

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Abstract

The assumption that AI-driven marketing technologies uniformly improve sales performance remains insufficiently tested. Using an exploratory synthetic firm-level dataset (n = 50), this study estimates OLS and quantile regressions at tau = 0.10, 0.25, 0.50, 0.75, and 0.90, with 2000-replication pairs-bootstrap inference. A data-integrity audit showed that marketing efficiency and revenue per salesperson are deterministic functions of revenue growth and were therefore excluded from the inferential models to prevent target leakage. In the corrected specification, automated lead generation is negatively associated with revenue growth in OLS and at Q75 and Q90, with 95% bootstrap confidence intervals excluding zero. AI usage, marketing budget, sales-team size, and personalized campaigns have wide bootstrap intervals that include zero at every reported quantile. Huber and ridge estimates preserve the OLS coefficient signs but differ in magnitude, underscoring the exploratory nature of the results. The study contributes a cautious, distribution-sensitive assessment and identifies priorities for validation with larger, real-world data.

Keywords AI-driven sales, Revenue growth, Quantile regression, Bootstrap inference, Robust regression

JEL Classification M31, O33, L86, C21

1 Introduction

Artificial intelligence (AI), machine learning (ML), and advanced data analytics have rapidly transformed the landscape of digital marketing and sales, triggering a substantial expansion in both academic research and practical applications [6]. In increasingly competitive and data-intensive business environments, firms are under growing pressure to adopt AI-driven technologies to enhance decision-making, improve operational efficiency, and sustain competitive advantage [1]. In this context, AI-powered marketing technologies have emerged as critical tools for optimizing sales force performance by automating routine processes, generating actionable customer insights, and enabling more precise, data-driven strategies [49, 50]. From predictive analytics to personalized outreach [45], AI is fundamentally reshaping sales operations and allowing sales teams to shift their focus toward higher-value activities such as relationship management and strategic planning [35].

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Traditional sales technologies, including sales force automation (SFA) and customer relationship management (CRM) systems, have evolved significantly with the integration of AI capabilities [7]. These enhanced systems facilitate more effective lead generation, improve forecasting accuracy, and streamline customer engagement processes [49, 50, 55]. By refining sales pipelines, prioritizing high-value prospects, and reducing inefficiencies in resource allocation, AI contributes to improved productivity and organizational responsiveness in dynamic market conditions [57]. As a result, AI adoption is often associated with superior sales performance and increased organizational agility.

Beyond operational efficiency, AI also plays a strategic role in shaping customer relationships and long-term value creation. Through large-scale data analysis, behavioral prediction, and personalized interaction design, AI supports customer loyalty strategies and enhances decision-making in product and market planning [31, 38, 56]. AI-driven segmentation enables firms to tailor their offerings more effectively, thereby improving customer satisfaction, retention, and conversion rates [44]. Importantly, the prevailing perspective in the literature conceptualizes AI not as a substitute for human sales agents but as a complementary technology that augments human capabilities [10]. By automating data-intensive tasks, AI enables sales professionals to focus on empathy-driven communication, complex negotiation, and relationship-building activities [19].

From a broader perspective, AI-driven marketing technologies can also be conceptualized as data-driven decision support systems that enhance managerial decision-making processes. This study is motivated by the need to move beyond the assumption that AI-driven marketing technologies automatically enhance sales performance. Although AI is widely presented as a source of efficiency, predictive accuracy, and improved decision support, managers still face uncertainty about whether these technologies generate the same value at different positions in the conditional revenue-growth distribution.

Despite these advancements, the assumption that AI adoption universally enhances sales performance remains insufficiently scrutinized. While AI systems excel at processing large datasets, identifying patterns, and forecasting customer behavior [37, 40], they may also introduce new challenges related to over-automation, misalignment with organizational processes, and reduced flexibility in decision-making. The human element, particularly emotional intelligence, trust-building, and contextual judgment, remains indispensable in complex sales environments [19, 41]. Consequently, the effectiveness of AI in sales is likely to depend not only on technological capabilities but also on how well these technologies are integrated with human expertise. The core problem addressed in this study is therefore not merely the limited empirical attention given to AI in sales contexts, but the lack of clarity about when AI enhances performance and when it may create diminishing returns through over-automation, weak organizational integration, or reduced reliance on human judgment.

Although research has documented AI applications in marketing, CRM, personalization, and forecasting [9, 10, 27, 32], three issues remain underdeveloped. First, most evidence is usually reported as a single average effect (aggregate) and therefore says little about how associations differ across the conditional distribution of sales performance. Second, studies often discuss implementation risks without testing whether the sign or magnitude of AI-related coefficients varies between lower- and upper-performing firms. Third, macroeconomic, industry, consumer, and organizational conditions are rarely

integrated into the same empirical framework. These omissions motivate a distributional, explicitly contingent analysis.

This study addresses the first two gaps by estimating how the associations of AI usage, automated lead generation, marketing budget, sales team size, and personalized campaigns vary across revenue-growth quantiles. Marketing efficiency is retained only as a descriptive diagnostic because the supplied measure is revenue growth divided by marketing budget and would therefore introduce target leakage if used as a regressor. The quantiles describe positions in the conditional distribution of revenue growth; they should not be interpreted as direct measurements of organizational age, industry life-cycle stage, or a firm's longitudinal development stage.

The study makes three bounded contributions. First, it reframes AI-driven marketing technologies as decision-support resources whose associations with performance may vary across the revenue-growth distribution. Second, it links this heterogeneity to dynamic-capability and socio-technical arguments about organizational fit and human-AI complementarity, while avoiding claims that the present data directly test those mechanisms. Third, it provides an exploratory simulation framework that makes omitted contextual factors and replication requirements visible. The contribution is therefore analytical and hypothesis-generating, not causal or population-representative.

The remainder of the paper is structured as follows. The next section reviews the relevant literature and develops the hypotheses. The methodology section then outlines the data and empirical approach, followed by separate Results and Discussion sections. Managerial and policy implications are presented before the study's limitations and a concise conclusion.

2 Literature review

Artificial intelligence (AI)-driven marketing technologies can be conceptualized as data-driven decision support systems (DSS) that augment managerial decision making. By processing customer and market data, AI tools may support sales and marketing decisions, but their associations with performance can vary across the conditional outcome distribution and across organizational contexts. Conditional quantiles are used here as distributional positions, not as measures of firm age or life-cycle stage.

The integration of artificial intelligence (AI) into sales and marketing has attracted significant scholarly attention in recent years, with a growing body of research examining its implications for sales force performance, customer engagement, and firm-level outcomes. Existing literature highlights multiple dimensions through which AI transforms marketing and sales processes, ranging from automation and predictive analytics to personalization and human–AI collaboration.

One of the earliest and most influential applications of AI in sales lies in the evolution of Sales Force Automation (SFA) and Customer Relationship Management (CRM) systems. Originally developed to streamline administrative tasks and organize customer data, these systems have evolved into AI-enhanced platforms incorporating predictive analytics and automated decision-making capabilities. Agnihotri [2] emphasizes the fragmented nature of research in this domain and calls for a comprehensive performance framework to evaluate returns on investments in CRM, digital media, and AI technologies. Similarly, Kumar et al. [28] argue that emerging technologies such as AI, machine learning, IoT, and blockchain significantly enhance CRM capabilities, while

Vignesh and Vasantha [58] highlight the transformative role of big data and analytics in overcoming the limitations of traditional CRM systems. Libai et al. [29] further suggest that AI-driven CRM systems improve customer acquisition, development, and retention by enabling more accurate predictions of customer lifetime value. Additionally, Liu-Thompkins et al. [30] introduce the concept of artificial empathy, emphasizing its potential to create value for customers and firms while also noting that it may be unnecessary or even harmful in some situations.

Predictive analytics represents another critical dimension of AI adoption in sales. By leveraging machine learning algorithms, firms can forecast demand, identify high-potential leads, and optimize resource allocation. Venkataramanan et al. [55] review AI-driven forecasting techniques in CRM systems and report that they can improve sales forecasting accuracy. At the same time, Enholm et al. [11] note that the value firms obtain from AI depends on technological, organizational, and environmental enablers and inhibitors of adoption and use. Amirkolaii et al. [5] show that AI-driven models outperform traditional forecasting methods in handling irregular demand patterns, particularly in service supply chains. Ruiz-Real et al. [47] further underscore the strategic importance of predictive analytics in digital marketing and business decision-making.

Automated lead generation has also emerged as a central focus in AI-driven sales research. Potla [43] identifies AI-powered lead generation systems as essential tools for enhancing customer targeting and improving conversion rates. Jayaweera and Farooq [23] demonstrate how AI automates labor-intensive processes and enhances customer engagement in the real estate sector. Similarly, Haleem et al. [15] and Umamaheswari [54] highlight the role of AI in enabling real-time personalization and targeted communication. Davenport et al. [10] describe how AI sales assistants can contact large numbers of leads and identify the most promising ones, which may accelerate lead qualification and expand sales pipelines. However, while these studies emphasize efficiency gains, they often overlook potential trade-offs related to lead quality and sales force overload.

In the domain of customer segmentation and personalization, AI plays a crucial role in enabling more refined and targeted marketing strategies. Kedi et al. [25] demonstrate how AI-driven tools enhance customer experience and sales performance in SMEs by delivering personalized recommendations. Huang and Rust [20] conceptualize "thinking AI" as a mechanism for enhancing segmentation and targeting strategies, thereby improving marketing effectiveness. Hicham et al. [17] further highlight the integration of predictive analytics, personalization, and conversational AI in shaping customer engagement. Despite these advancements, the empirical evidence on the performance impact of personalization remains mixed, suggesting the need for further investigation.

A growing stream of literature emphasizes the importance of human–AI synergy in achieving optimal performance outcomes. Petrescu and Krishen [42] argue that combining human creativity with AI's analytical capabilities leads to superior marketing performance. Sankaran et al. [48] highlight the importance of human oversight in algorithmic decision-making to avoid suboptimal outcomes driven by purely data-centric approaches. Hemmer et al. [16] conceptualize human–AI complementarity through capability and information asymmetries, while Simón et al. [51] demonstrate how team-level interactions enhance value creation in AI-integrated environments. Revilla et al.

[46] and Peng et al. [41] further emphasize that human intervention remains essential in contexts requiring empathy, trust, and relational depth.

Dynamic capabilities theory provides one explanation for why the value of AI may be contingent. AI can support sensing, seizing, and transforming activities, but performance gains depend on complementary routines, managerial coordination, and the capacity to reconfigure resources [51, 52, 59]. From this view, AI adoption alone is not a capability,value arises when technology is integrated into an adaptive organizational system.

Socio-technical and human-AI complementarity perspectives similarly emphasize joint optimization of technical tools, work design, and human judgment. Human oversight can be especially important when customer interactions require empathy, trust, or contextual knowledge [16, 41, 42]. These perspectives support organizational-fit interpretations of heterogeneous coefficients, but the current variables do not directly observe integration quality, automation intensity, or human override behavior.

Sales performance is also shaped by context outside the focal marketing technologies. Economic policy uncertainty can alter investment, demand, financing conditions, and firm performance [8], while geopolitical and business uncertainty may change customer acquisition costs and purchase timing. At the market level, consumer perceptions and buying attitudes, as emphasized by the theory of planned behavior [4], interact with industry maturity, competition, and product involvement. Because these factors are not represented in the simulation, they remain plausible omitted variables rather than controlled influences.

Taken together, the literature supports a narrower research question: do the estimated associations between AI-related marketing variables and revenue growth differ across conditional quantiles, after accounting for the included firm-level variables? The study does not test a universal technology effect, a causal growth-stage transition, or the proposed organizational mechanisms directly.

3 Hypotheses development

Building on the theoretical foundations and empirical insights discussed above, this study develops the following hypotheses:

H1: Marketing budget positively influences revenue growth across all firm growth levels.

H2: An independently measured marketing-efficiency construct is positively associated with revenue growth.

H3: Sales team size positively affects revenue growth, particularly in low-to-medium growth quantiles.

H4: Automated lead generation is negatively associated with revenue growth in higher-growth quantiles, a pattern that may be consistent with diminishing returns or lead-quality constraints.

H5: The association between AI usage and revenue growth varies across quantiles and may be negative in upper quantiles; organizational misalignment and over-automation are possible, unmeasured interpretations.

H6: Personalized campaigns have no significant impact on revenue growth, implying market saturation or limited differentiation effects.

4 Data and methodology

4.1 Data

The analysis uses a stylized, country-neutral and cross-industry simulation of 50 firms. The observations were not drawn from a specific country, sector, platform, customer segment, or historical period. Accordingly, the data represent a controlled analytical setting rather than a statistically representative business population. Revenue growth is the dependent variable; the inferential predictors are sales team size, AI-based predictive-analytics usage, personalized campaigns, marketing budget, and automated lead generation (Table 1).

Synthetic data are useful when access to confidential firm-level records is restricted, but their value depends on a fully documented data-generating process [13, 24, 53]. The supplied workbook contains 50 complete row-level observations with no duplicate rows. It does not include the original generation seed, distribution families and parameters, target dependence structure, truncation rules, or generator code, those elements of the simulation cannot be independently verified.

The verifiable transformation sequence is as follows. Revenue growth, AI usage, and automated lead generation remain in percentage units. Natural logarithms are applied to sales team size, personalized campaign count, and marketing budget. The workbook also contains revenue per salesperson (Revenue Growth/Sales Team Size) and marketing efficiency (Revenue Growth/Marketing Budget). Because both measures contain the dependent variable by construction, they are reported only as data-audit diagnostics and excluded from every inferential regression.

Figures 1, 2, 3, 4, 5, 6, 7, 8 and 9 and Table 2 document the realized marginal distributions and pairwise relationships. The bounded sample does not reproduce the heavy tails, structural breaks, measurement error, sector clustering, or rare shocks that may occur in real firm data. Correlations involving marketing efficiency or revenue per salesperson are partly mechanical because those ratios contain revenue growth; they are not interpreted as independent empirical relationships.

The row-level dataset and the analysis code are sufficient to reproduce the transformations, corrected regressions, bootstrap estimates, robustness checks, tables, and new figures reported here. Exact regeneration of the original synthetic observations still requires the original random seed, per-variable distributions and parameters, target

Table 1 Variables and measurement units

Variable	Description	Unit
Rev_Growth	Growth rate of revenue over a period	% (Percentage)
Sales_Team	Number of sales team members	Count
AI_Usage	AI-driven predictive analytics usage	% (Percentage)
Mkt_Budget	Total marketing budget allocated	$ (USD)
Lead_Gen	Percentage of automated lead generation	% (Percentage)
Mkt_Eff	Revenue growth divided by marketing budget (diagnostic only; excluded from regressions)	Ratio
Pers_Camp	Number of personalized marketing campaigns	Count
Rev_Per_Sales	Revenue growth divided by sales-team size (diagnostic only; excluded from regressions)	Percentage points per salesperson

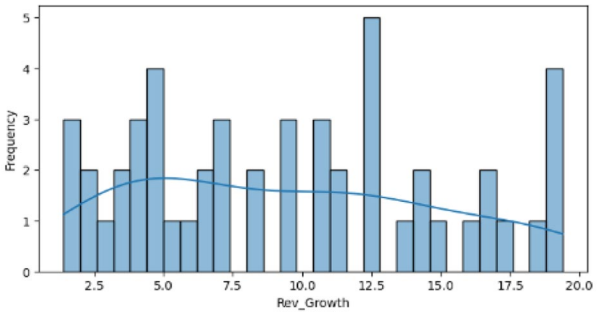


Fig. 1 Distribution of Rev_Growth

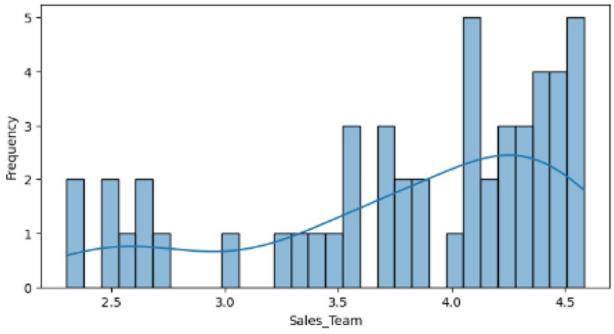


Fig. 2 Distribution of Sales_Team

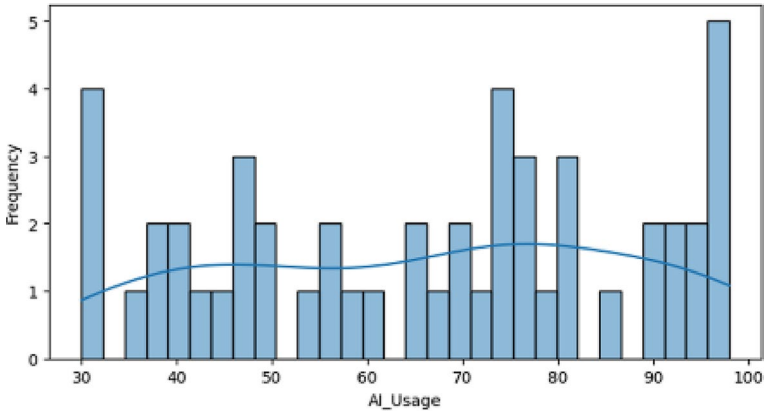


Fig. 3 Distribution of AI_Usage

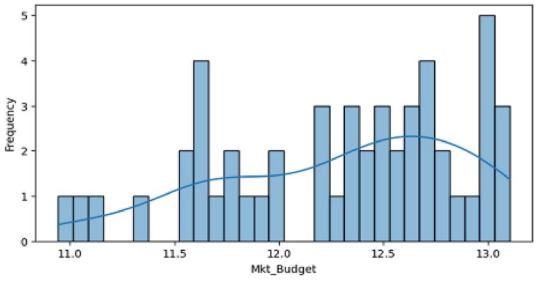


Fig. 4 Distribution of Mkt_Budget

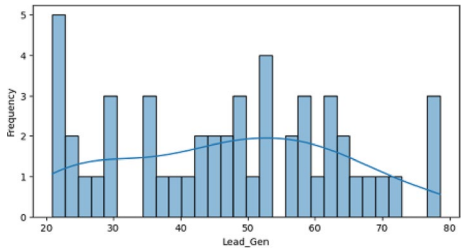


Fig. 5 Distribution of Lead_Gen

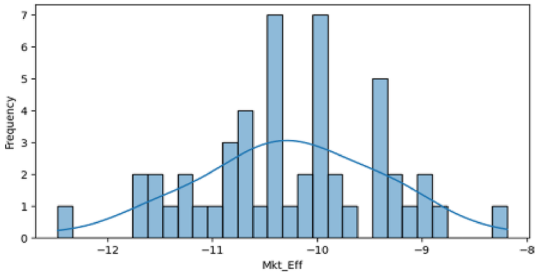


Fig. 6 Distribution of Mkt_Eff

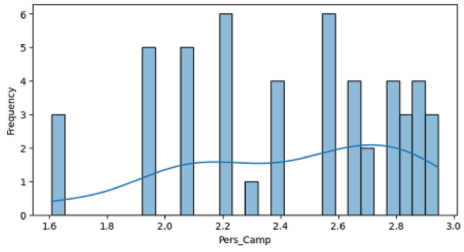


Fig. 7 Distribution of Pers_Camp

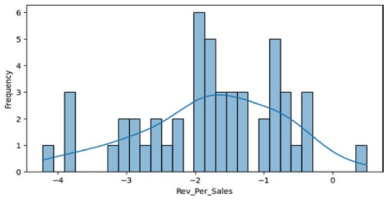


Fig. 8 Distribution of Rev_Per_Sales

correlation matrix, dependence algorithm, redraw or truncation rules, and software environment, which were not supplied.

Synthetic data provide analytical control but do not substitute for external validation. The results are therefore treated as an exploratory demonstration of model- and quantile-sensitive associations and should be tested in larger longitudinal, multi-industry, and country-specific datasets.

The definitions and measurement units of the variables used in the analysis are presented in Table 1.

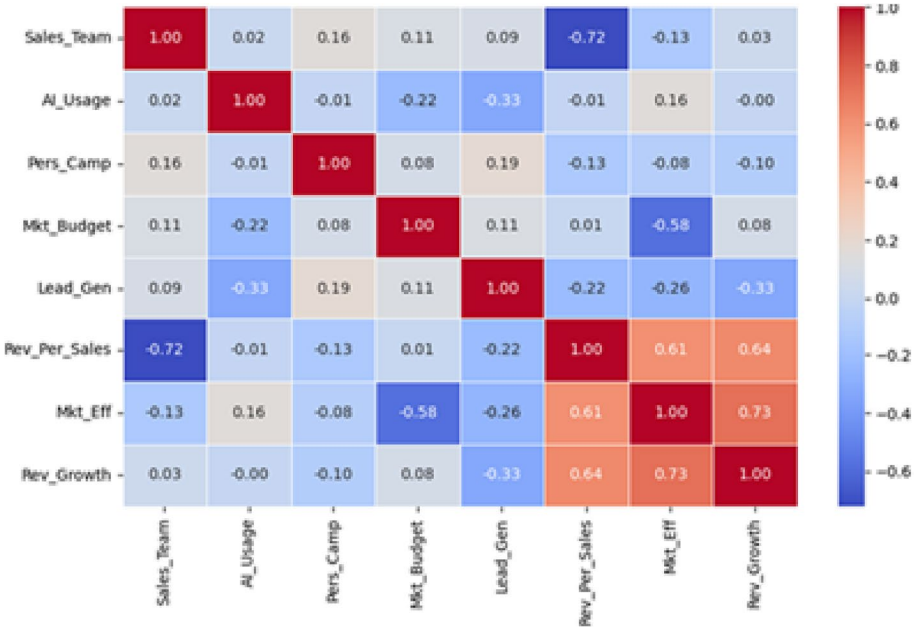


Fig. 9 Correlation matrix

Table 2 Descriptive statistics

Variable	Mean	Std. Dev	Minimum	Maximum
Rev_Growth	9.480	5.485	1.400	19.400
Sales_Team	3.808	0.689	2.303	4.585
AI_Usage	66.120	21.590	30.000	98.000
Mkt_Budget	12.298	0.586	10.943	13.104
Lead_Gen	47.434	16.556	20.900	78.600
Mkt_Eff	− 10.261	0.873	− 12.476	− 8.188
Pers_Camp	2.428	0.383	1.609	2.944
Rev_Per_Sales	− 1.771	1.031	− 4.217	0.495

4.2 Method

To capture the heterogeneous effects of AI-driven marketing technologies across firms with different performance levels, this study employs quantile regression. Unlike ordinary least squares (OLS), which estimates the conditional mean of the dependent variable, quantile regression enables the estimation of conditional quantiles, thereby providing a more comprehensive understanding of the distributional dynamics of revenue growth. This approach is particularly appropriate in the presence of non-normal error distributions, heteroskedasticity, and potential outliers [26].

Formally, the quantile regression model is defined as:

$$Q_{Y_i}(\tau|X_i) = X_i'\beta(\tau) \tag{1}$$

where $Q_{Y_i}(\tau|X_i)$ denotes the conditional τ-th quantile of the dependent variable given the covariates X_i, and $\beta(\tau)$represents the vector of quantile-specific coefficients. When τ=0.5, the model corresponds to the conditional median.

The parameter estimates are obtained by minimizing the following objective function:

$$\hat{\beta}(\tau) = \arg min_{\beta} \sum_{i=1}^{n} \rho_{\tau}(Y_i - X_i'\beta) \tag{2}$$

where $\rho_{\tau}(u)$ is the quantile loss function defined as:

$$p_{\tau}(u) = u(\tau - \| \{u < 0\}) = \begin{cases} \tau u if u \geq 0 \\ (\tau - 1) u if u < 0 \end{cases} \tag{3}$$

This asymmetric loss function assigns different weights to positive and negative residuals, allowing the estimation of different points across the conditional distribution. To examine distributional heterogeneity, the model is estimated at tau = 0.10, 0.25, 0.50, 0.75, and 0.90. These estimates describe lower, middle, and upper positions in the conditional revenue-growth distribution; they do not identify longitudinal firm-growth stages.

The empirical specification of the model is given by:

$$\begin{aligned} Q_{\text{RevGrowthit}}(\tau|X_{it}) = {} & \alpha_0(\tau) + \alpha_1(\tau)\,\text{SalesTeam}_{it} + \alpha_2(\tau)\,\text{AIUsage}_{it} \\ & + \alpha_3(\tau)\,\text{PersCamp}_{it} + \alpha_4(\tau)\,\text{MktBudget}_{it} + \alpha_5(\tau)\,\text{LeadGen}_{it} \end{aligned} \tag{4}$$

In this specification, the coefficients $\alpha j(\tau)$vary across quantiles, capturing how the marginal effects of explanatory variables differ across the distribution of revenue growth.

With five regressors and n = 50, Q10 and Q90 are informed by few tail observations. Inference therefore uses a nonparametric pairs bootstrap with 2000 replications and fixed seed 20, 260, 723; percentile 95% confidence intervals are reported for OLS and every quantile. Model specificity is assessed with Huber robust regression [21] and ridge regression [18]. Predictors are standardized for the cross-estimator comparison, and the ridge penalty is selected by generalized cross-validation over alpha values from 10^{-4} to 10^{4}.

5 Results

Revenue growth, AI usage, and automated lead generation are expressed in percentage points; sales team size, marketing budget, and personalized campaign count enter in natural logarithms. The resulting log-level coefficients are semi-elasticities: a 1% increase in a logged predictor corresponds approximately to beta/100 percentage points of revenue growth, holding the other predictors constant. Table 2 reports descriptive statistics for the transformed variables, including the two diagnostic ratios that are excluded from inferential models.

Figures 1, 2, 3, 4, 5, 6, 7 and 8 illustrate the empirical distributions of the supplied variables. The figures describe the realized synthetic sample only. Revenue growth (Fig. 1) shows an even spread without a dominant peak, indicating that firms at both the lower and upper ends differ significantly, justifying the use of quantile regression.

In terms of predictors, AI usage (Fig. 3) and automated lead generation (Fig. 5) exhibit broad variation with few firms at the extremes, suggesting that the lack of a bootstrap-supported association for AI usage isn't due to limited adoption variability. However, sales team size (Fig. 2) and marketing budget (Fig. 4) are left-skewed. Personalised campaigns (Fig. 7) have a narrow range, leading to fewer informative observations, which may explain the wide bootstrap confidence intervals and the sign changes noted in Table 3, aligning with the unsupported hypotheses H1, H3, and H6.

Table 3 Model estimation results

Dependent variable: Rev_Growth						
Variables	**Model: OLS**	**Model: quantile regression**				
		Quantiles				
		0.10	**0.25**	**0.50**	**0.75**	**0.90**
Intercept	6.424	2.424	2.582	13.824	2.877	26.251
	(17.425)	(13.875)	(18.715)	(23.376)	(28.920)	(29.403)
Sales_Team	0.545	− 1.920	− 1.477	3.813	2.160	− 2.519
	(1.109)	(1.130)	(1.845)	(1.797)	(2.028)	(2.524)
AI_Usage	− 0.028	0.001	− 0.015	− 0.040	0.003	− 0.058
	(0.037)	(0.040)	(0.045)	(0.053)	(0.061)	(0.064)
Mkt_Budget	0.835	0.371	0.734	0.087	1.258	0.964
	(1.345)	(1.159)	(1.460)	(1.733)	(2.292)	(2.266)
Lead_Gen	− 0.123*	− 0.024	− 0.064	− 0.166	− 0.183*	− 0.244*
	(0.049)	(0.055)	(0.070)	(0.071)	(0.067)	(0.081)
Pers_Camp	− 0.662	2.058	1.105	− 3.794	− 2.274	1.561
	(2.127)	(2.762)	(3.918)	(2.841)	(2.563)	(2.702)

Coefficients are followed by pairs-bootstrap standard errors in parentheses (2,000 replications; seed = 20,260,723). * indicates that the percentile 95% bootstrap confidence interval excludes zero. OLS R-squared = 0.137; adjusted R-squared = 0.039. Breusch-Pagan LM = 10.799 ($p = 0.056$); Durbin-Watson = 2.435; Jarque–Bera = 1.136 ($p = 0.567$)

Lastly, marketing efficiency (Fig. 6) and revenue per salesperson (Fig. 8) are more symmetric but should not be considered well-behaved independent measures since their distributions are partly influenced by revenue growth in Fig. 1. They are included solely for data documentation and are excluded from further inferential models.

Figure 9 presents the correlation matrix as a data-audit display. The apparent relationships of revenue per salesperson and marketing efficiency with revenue growth are mechanically induced by their formulas. Consequently, neither derived measure is included in the corrected OLS, quantile, Huber, or ridge models.

Table 3 reports the corrected OLS and quantile-regression estimates with revenue growth as the dependent variable. The supplied workbook reproduces the manuscript's previous coefficients exactly when marketing efficiency is included, but that specification attains R-squared = 0.935 largely because log(Marketing Efficiency) = log(Revenue Growth)—log(Marketing Budget). The corrected model excludes both dependent-variable-derived ratios. Its OLS R-squared is 0.137 (adjusted R-squared = 0.039), which is a more credible representation of the limited explanatory content of this small synthetic sample.

For the corrected OLS model, the Breusch-Pagan statistic is 10.799 ($p = 0.056$), the Durbin-Watson statistic is 2.435, and the Jarque–Bera statistic is 1.136 ($p = 0.567$). Variance inflation factors range from 1.042 to 1.176, well below the commonly used threshold of 10 [14]. These diagnostics do not reject homoskedasticity or normality at the 5% level and show no material multicollinearity, although the near-threshold Breusch-Pagan result and small sample further motivate bootstrap inference.

Table 3 shows that automated lead generation is the only predictor whose bootstrap confidence intervals exclude zero. Its coefficient is negative in OLS (− 0.123) and at every quantile. The 95% percentile interval excludes zero in OLS [− 0.211, −0.022], at Q75 [− 0.301, −0.024] and at Q90 [− 0.320, −0.002]. The coefficient grows in absolute size from Q10 (− 0.024) to Q90 (− 0.244), so the negative association appears stronger in the upper part of the conditional revenue growth distribution (Fig. 10).

The analysis shows that AI usage has small coefficients that vary in sign across different parts of the distribution. Specifically, the coefficients are negative in OLS, Q25,

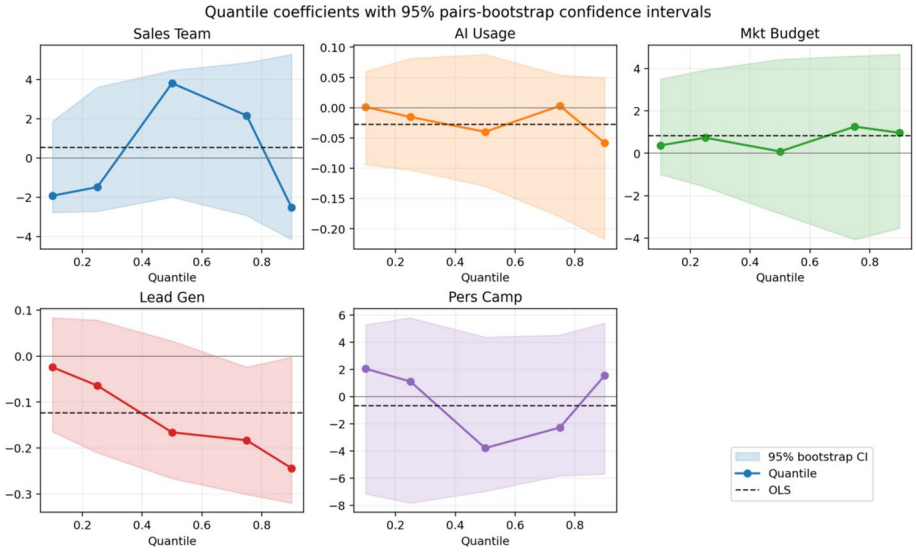


Fig. 10 Quantile coefficients with 95% pairs-bootstrap confidence intervals

Table 4 Alternative-estimator comparison (standardized coefficients)

Variable	OLS	Huber	Ridge
Sales_Team	0.068	0.265	0.017
AI_Usage	− 0.108	− 0.130	− 0.013
Mkt_Budget	0.089	0.057	0.031
Lead_Gen	− 0.372	− 0.474	− 0.120
Pers_Camp	− 0.046	− 0.215	− 0.029

Predictors and the dependent variable are standardized for this comparison. Huber uses epsilon = 1.35. Ridge alpha = 89.074, selected by generalized cross-validation. All predictor signs are identical across OLS, Huber, and ridge; magnitudes are estimator-sensitive

Q50, and Q90, while they are slightly positive in Q10 and Q75. Importantly, all intervals, including Q90, encompass zero [− 0.218, 0.049]. In contrast, the marketing budget yields positive point estimates in OLS and across all five quantiles, although all confidence intervals still include zero. The sizes of sales teams and personalised campaigns exhibit sign changes across quantiles, and their intervals remain wide, consistently including zero in every model.

In Table 4 and Fig. 11, a comparison is made between the standardised estimates from OLS and those from Huber and ridge regression. Each of the five predictors retains the same sign across all three estimation methods: both sales team size and marketing budget have positive coefficients, while AI usage, automated lead generation, and personalized campaigns are negative. However, the magnitude of these coefficients differs. Ridge regression (with an alpha of 89.074) significantly decreases all coefficients, while Huber estimates are generally larger in absolute terms than OLS for four out of the five predictors. Notably, automated lead generation consistently shows the largest standardized coefficient across all three estimation techniques.

Table 5 summarises how each hypothesis is assessed against these aforementioned results.

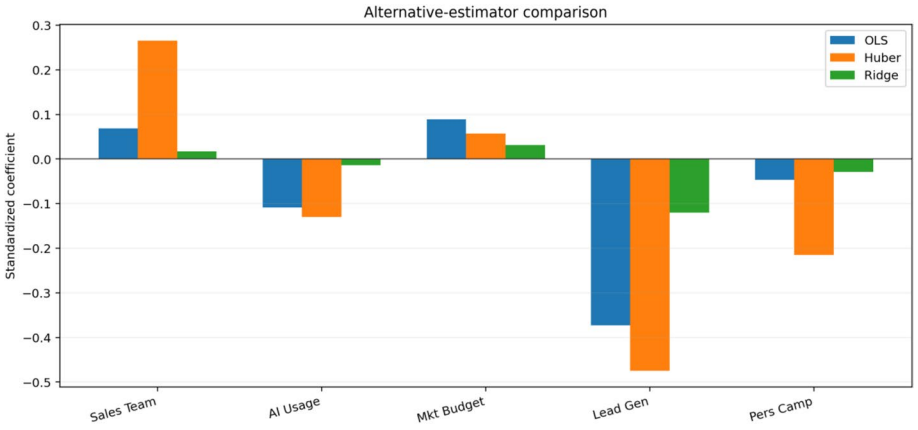


Fig. 11 Standardized OLS, Huber, and ridge coefficients

Table 5 Hypothesis assessment

Hypothesis	Evidence from the reported models	Assessment
H1	Mkt_Budget is positive in OLS and all quantiles, but every 95% bootstrap CI includes zero	Not supported
H2	Mkt_Eff equals Rev_Growth / Mkt_Budget and was excluded to prevent target leakage	Not testable with available measure
H3	Sales_Team changes sign across quantiles and every 95% bootstrap CI includes zero	Not supported
H4	Lead_Gen is negative throughout; 95% bootstrap CIs exclude zero in OLS, Q75, and Q90	Supported at Q75 and Q90; also supported in OLS
H5	AI_Usage is negative at Q90 but slightly positive at Q75; all bootstrap CIs include zero	Not supported
H6	Pers_Camp is imprecisely estimated and all bootstrap CIs include zero; this does not prove a zero effect	Consistent with no detected effect

6 Discussion

Looking at the results, it seems that neither the marketing budget nor the sales team size (H1 and H3) received sufficient support. While the marketing budget shows positive point estimates across all quantiles, which aligns with expectations, none of the confidence intervals exclude zero. This may indicate that the relationship between marketing expenditure and sales isn't linear. Agrahari et al. [3], in their study of publicly listed manufacturing companies in Nepal, highlight a non-linear relationship wherein a specific level of marketing investment optimises sales. A single logged budget term may not effectively capture such a pattern. Additionally, the budget variable reflects a limited number of firms on the lower end (Fig. 4), which restricts the available data. The sales team size exhibits varying signs across quantiles, suggesting that the data does not consistently support the hypothesis (H3) that larger sales teams correlate with greater growth in the low to mid quantiles.

On the other hand, H4 is supported at the 75th and 90th percentiles. Much of the existing literature suggests that automated lead generation enhances efficiency by streamlining lead qualification and expanding sales pipelines [10, 23]. However, the current findings do not align with this expectation. Instead, they resonate more with studies focusing on lead quality and the follow-up processes post-lead generation. Huttelmaier and Heigl [22] note that companies employing marketing and sales automation

frequently overwhelm sales staff with low-quality leads, which diverts their time from leads that could convert. Furthermore, Ohiomah et al. [36] found that lead management systems influence inside sales performance through various factors such as lead follow-up intensity, adaptive selling, and salesperson skills. This implies that the effectiveness of such systems is contingent upon lead handling rather than sheer lead volume. Consequently, a higher proportion of automated leads may merely increase volume without contributing to revenue. However, the data do not assess lead quality or sales workload, leaving this as a tentative interpretation. There remains a gap in understanding why the correlation is more pronounced in the upper quantiles,one explanation worth exploring is that faster-growing companies may have less capacity to handle additional low-quality leads.

Regarding AI usage (H5), there is no support for this hypothesis. The coefficients for AI usage are relatively small, show varying signs across quantiles, and all confidence intervals include zero. There is considerable variability in AI usage among firms (Fig. 3), so this outcome cannot be attributed solely to insufficient variation. Existing studies on AI transformation projects indicate that AI can enhance process and organisational performance [59]. Yet, reviews suggest that firms continue to struggle to extract value from AI, with adoption often influenced by various organisational factors [11]. Evidence from case studies indicates that the success of AI is largely dependent on the synergy between people and systems. Simón et al. [51] connect value creation to factors such as interoperability and mutual trust between humans and AI. Moreover, Revilla et al. [46] found that human involvement significantly enhances AI forecasts, particularly under conditions of low uncertainty and extended time horizons. Conversely, Papagiannidis et al. [39] documented the unintended consequences of AI adoption regarding work dynamics, conflicts, and accountability. Taken together, these insights suggest that the lack of a consistent association indicates that the proportion of AI activities may not be a reliable measure of AI's integration into sales processes. The current data do not clarify whether issues stem from over-automation or inadequate integration. As for personalised campaigns (H6), the results only align loosely with this hypothesis, as no significant relationship was observed. The literature on personalisation presents mixed evidence, with some studies indicating advantages for customer experience and sales within SMEs [25].

These findings provide contributions in three key areas. First, most existing research on AI in marketing and sales derives from reviews, conceptual analyses, and studies reporting average effects [9, 32, 34]. Quantile regression studies on firm performance reveal that the drivers of success can differ markedly between firms with lower and higher sales. For instance, Matekenya and Moyo [33] discovered that R&D investments bolster performance in South African SMMEs with higher sales, while product and service innovation is more critical for those with lower sales. Similarly, Ghardallou [12] reports that the adverse effect of leverage on performance is stronger among more profitable listed firms in Saudi Arabia. This study applies a similar approach to explore AI marketing variables and finds that, in this sample, significant differences appear only for automated lead generation. Second, the data audit demonstrates that efficiency ratios constructed from dependent variables can lead to misleadingly high model fits, a consideration pertinent to studies relying on ratio-based performance indicators. Finally, the results provide indirect backing for the perspective within the dynamic capabilities

and human-AI complementarity literature that mere AI adoption does not guarantee enhanced performance [51, 52].

7 Managerial and policy implications

Managers should not infer a universal numerical 'optimal AI level' from these cross-sectional synthetic coefficients. Instead, the optimal adoption level should be treated as a firm-specific decision threshold established through staged pilots. Before deployment, managers should define a baseline and pre-specified success criteria for incremental revenue, conversion, forecast error, lead-acceptance rate, sales-cycle time, salesperson workload, customer complaints, and human override frequency.

A practical scale-or-stop rule is to expand AI only when the pilot's incremental contribution remains positive after total technology, integration, training, and monitoring costs and when lead quality and customer-experience indicators do not deteriorate. Managers should pause or redesign deployment when marginal revenue falls, lead rejection or override rates rise, sales-cycle time lengthens, or adverse customer indicators persist for two review periods. Controlled holdout groups and confidence intervals are preferable to selecting a cutoff from the present quantile coefficients.

Governance should also be contingent on organizational readiness. Lower-performing firms may first strengthen data quality, measurement, and core sales routines; firms with more developed systems should emphasize integration, decision rights, human escalation paths, and continuous monitoring. Lead-generation automation should be governed by downstream conversion and capacity metrics rather than lead volume alone.

For policy makers, the findings support capability-building and responsible-AI frameworks rather than uniform adoption targets. Transparency, auditability, data protection, worker training, and access to testing resources can help firms evaluate AI under sector-specific market, consumer, and uncertainty conditions.

8 Limitations and future research

As is the case with any study, this study has several limitations. First, it utilizes a small, cross-sectional synthetic sample with n = 50 and five regressors, making Q10 and Q90 sensitive to individual observations despite 2000 bootstrap replications. Second, marketing efficiency and revenue-per-salesperson measures, being deterministic functions of revenue growth, were excluded from inferential models, preventing the testing of H2. Third, while Huber and ridge estimates maintain coefficient directions, the ridge solution is heavily shrunk, and the design does not support causal inference or generalization. Additionally, the simulation lacks industry, country, customer segment, or time frame specificity, limiting its ability to capture sector dynamics, market maturity, or anomalies. To ensure reproducibility, all relevant details such as the generator and seed must be archived.

Moreover, the model overlooks external factors like economic uncertainty, inflation, and competitive intensity, leading to potential omitted-variable bias in relation to AI investment and sales performance. Future studies should incorporate macroeconomic and industry controls and examine interactions with AI adoption [8]. Consumer perceptions, attitudes, trust, and privacy concerns are also not addressed, even though they can impact responses to personalization and automation [49, 50]. A multi-source

approach that integrates data from firms, salespeople, and customers would strengthen the findings.

Lastly, the study fails to measure crucial concepts like over-automation, integration failures, and digital maturity. These interpretations of coefficient patterns remain unobserved mechanisms. Future research should employ longitudinal or experimental designs and formal mediation tests to explore these factors.

9 Conclusion

This corrected exploratory analysis finds a negative association between automated lead generation and revenue growth in OLS and at Q75 and Q90, with percentile 95% bootstrap intervals excluding zero. For AI usage, marketing budget, sales-team size, and personalized campaigns, the bootstrap intervals include zero at all reported quantiles.

The results do not establish that over-automation, integration failure, lead quality, or any other mechanism caused lower performance. They identify one lead-generation pattern that requires direct measurement and external validation. Managers should therefore use staged pilots, marginal-return and quality metrics, and human-oversight indicators rather than a universal AI adoption threshold.

The principal next step is validation in larger, longitudinal, industry-specific data that include macroeconomic, consumer, organizational, lead-quality, and implementation-context measures. The original simulation generator and seed should also be deposited so that the synthetic sample itself, not only the reported analysis, can be regenerated.

Author contributions

Author 1 (C.S): Conceptualization, Methodology, Formal analysis, Writing—original draft. Author 2 (CdB): Data curation, Validation, Writing—review & editing. Author 3 (R.K): Supervision, Conceptualization, Writing—review & editing. Author 4 (E.K): Investigation, Resources, Visualization. Author 5 (S.Y): Writing—review & editing, Validation.

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Data availability

The row-level synthetic dataset and executable analysis code accompany this revision and reproduce the transformations, corrected regressions, 2,000-replication bootstrap, robustness checks, tables, and figures. The original data-generation seed, distribution parameters, dependence algorithm, and generator code were not supplied; exact regeneration of the synthetic observations is therefore not possible from the available materials.

Declarations

Ethics approval and consent to participate

Not applicable. This study does not involve human participants, human data, or human tissue.

Consent for publication

Not applicable.

Clinical trial number

Not applicable.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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